

Enhancing Accessibility for Visually Impaired Users through a Hybrid Real-Time Multi-Object Recognition System

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Abstract

Visual impairment creates substantial challenges in performing object recognition tasks essential for independent living. Existing assistive vision systems typically rely on either classical computer vision techniques or deep learning models, limiting their robustness and practical applicability in real-world environments. To address these limitations, this study proposes a hybrid intelligent vision framework that integrates YOLOv8-based object detection for robust object localization, barcode recognition for reliable product verification, and ORB feature matching for fine-grained identification when barcode information is unavailable, thereby combining the complementary strengths of deep learning and classical computer vision. The dataset was designed to represent four common information-access tasks encountered by visually impaired individuals, including product labels, Thai banknotes, short shelf-life food products, and pharmaceutical items. An expanded dataset comprising 1,105 object classes and 7,927 images was constructed under diverse environmental conditions. The complete recognition pipeline was evaluated as an integrated mobile assistive system through both controlled and uncontrolled experiments to assess recognition accuracy, robustness, and the feasibility of practical deployment. Experimental results show that the proposed framework achieved 97.6% recognition accuracy, outperforming both the ORB-Barcode baseline (96.2%) and the standalone YOLOv8 model (97.0%), while maintaining near-real-time performance with an average processing time of 2.30 s per inference. User evaluation further demonstrated statistically significant improvements in task success rates among trained participants. The proposed framework improves recognition robustness while preserving computational efficiency on resource-constrained mobile devices, providing a practical, scalable, and user-validated assistive solution that enhances accessibility and supports independent living for visually impaired individuals.

Keywords: Assistive technology, Computer vision, Mobile computing, Object recognition, Visually impaired



INTRODUCTION

Visual impairment remains a significant global challenge affecting independence, accessibility, and quality of life. According to the World Health Organization (WHO), millions of people worldwide experience blindness or moderate-to-severe vision impairment, creating barriers to information access, mobility, and participation in daily activities [1]. In Thailand, disability-inclusive development has become an important national priority, with recent reports emphasizing the need for technological solutions that support independent living, employment opportunities, and equitable access to services for persons with disabilities [2], [3]. These challenges highlight the growing demand for practical assistive technologies that provide reliable real-time information in everyday environments. Among the daily challenges faced by visually impaired individuals are identifying consumer products, recognizing banknotes, verifying food expiration dates, and distinguishing pharmaceutical products, all of which rely heavily on visual information.

Computer vision technologies have emerged as promising solutions for addressing these challenges. Traditional recognition systems employed handcrafted feature descriptors such as SIFT, SURF, and ORB for object identification and image matching [4], [5], [6]. Barcode-based approaches have also demonstrated effectiveness in assistive applications for product identification and information access [7], [8], [9]. More recently, deep learning-based object detection frameworks, including YOLO and transformer-based architectures, have significantly improved recognition performance under complex environmental conditions [10], [11], [12]. However, each approach exhibits inherent limitations. Feature-based methods are sensitive to occlusion and viewpoint variation, barcode recognition depends on visible machine-readable labels, and deep learning models may require additional verification mechanisms for fine-grained object identification. Consequently, integrating complementary recognition techniques offers a promising strategy for improving robustness without sacrificing computational efficiency on mobile platforms.

Recent studies have demonstrated the potential of computer vision technologies for supporting visually impaired individuals. Machine learning and deep learning-based assistive systems have been applied to object recognition and environmental awareness tasks [13], [14], [15], [16], while domain-specific solutions have been developed for Thai banknote recognition [17] and pharmaceutical identification [18]. Nevertheless, most existing studies address only a single recognition task or object category, limiting their applicability in realistic assistive scenarios where multiple object types must be recognized within a unified framework.

To address these limitations, this study extends the authors' previous ORB- and barcode-based assistive recognition system [19] by incorporating YOLOv8 as a robust object localization module while preserving the efficient fine-grained verification capabilities of barcode decoding and ORB feature matching. The proposed system integrates object detection, barcode decoding, and ORB feature matching to support robust multi-object recognition on mobile devices. The framework is designed to support four practical application domains: product label identification, Thai banknote recognition, expiration-date verification, and pharmaceutical product identification. Thai banknote recognition is based on the current banknotes series BE 2561 issued by the Bank of Thailand [20].

The main contributions of this study are threefold. First, a hybrid vision framework combining YOLOv8 object detection, barcode recognition, and ORB feature matching is proposed to improve recognition robustness under

practical operating conditions. Second, a multi-category dataset comprising 1,105 object classes and 7,927 images was constructed to support assistive recognition tasks. Third, the proposed framework was evaluated through both technical performance analysis and user-centered experimentation involving visually impaired participants under controlled and uncontrolled environments. The findings demonstrate that the proposed hybrid architecture effectively bridges deep learning-based object localization and classical fine-grained recognition, providing a scalable and practical assistive vision solution for real-world mobile applications.

LITERATURE REVIEW

1. Computer Vision-Based Recognition Technologies

Computer vision technologies have become increasingly important in assistive systems for visually impaired individuals because they enable automatic recognition and interpretation of objects within everyday environments. Traditional recognition approaches primarily rely on handcrafted local features, including Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), and Oriented FAST and Rotated BRIEF (ORB). Lowe [4] introduced SIFT to provide robust feature extraction under scale and rotation variations, while Bay et al. [5] improved computational efficiency through the SURF algorithm. Subsequently, Rublee et al. [6] proposed ORB, which combines FAST keypoint detection and BRIEF descriptors to achieve efficient feature matching suitable for real-time and resource-constrained applications. Although these techniques have demonstrated effectiveness in object recognition and image matching, their performance may deteriorate under severe occlusion, motion blur, complex backgrounds, and significant viewpoint variations, making them less suitable for robust assistive applications operating in unconstrained real-world environments.

Barcode-based recognition techniques have also been widely adopted in assistive applications because of their high accuracy and low computational requirements. Jethjarurach and Limpiyakorn [7] developed a mobile barcode reader to support product identification for visually impaired users, whereas Fernandcz et al. [8] proposed an image-based barcode detection and recognition framework capable of providing auditory feedback. In a comprehensive review, Pradhan et al. [9] highlighted the effectiveness of barcode recognition systems for real-time identification tasks and emphasized their suitability for deployment on mobile platforms. Despite these advantages, barcode-based methods remain dependent on the presence and visibility of machine-readable labels, making them vulnerable to label damage, occlusion, poor illumination, and unfavorable viewing angles. Consequently, barcode recognition alone cannot provide complete support for diverse real-world assistive scenarios.

Recent advances in deep learning have significantly improved object recognition and detection capabilities. Redmon et al. [10] introduced the YOLO framework, which reformulated object detection as a single-stage regression problem and enabled real-time object detection with competitive accuracy. He et al. [11] subsequently proposed deep residual networks (ResNet), facilitating the effective training of deep neural architectures and substantially improving image recognition performance. Carion et al. [12] further advanced object detection through the Detection Transformer (DETR), which integrates transformer architectures into an end-to-end detection framework. Building upon these developments, modern YOLO architectures have achieved an effective balance between detection accuracy, inference speed, and computational efficiency, making them particularly suitable for mobile and real-time applications. Nevertheless, category-level object detection alone may be insufficient for



assistive scenarios requiring fine-grained identification of visually similar products, medications, or currency denominations. Consequently, additional verification mechanisms are often necessary to improve recognition reliability in practical deployment environments. This limitation motivates the integration of complementary recognition techniques rather than relying solely on deep learning-based detection.

2. Assistive Technologies for Visually Impaired Individuals

Numerous assistive technologies have been developed to enhance independence and accessibility for visually impaired individuals. Recent studies have demonstrated the effectiveness of computer vision and machine learning techniques in supporting object recognition and environmental awareness. For example, Munia and Taher [13] applied machine learning-based object detection to assist visually impaired users in identifying surrounding objects, while Aduri and Naganjaneyulu [14] reviewed recent advancements in computer vision-based assistive technologies and highlighted their potential to improve accessibility and independent living. Similarly, Bhandari et al. [15] demonstrated that deep learning-based object recognition can provide accurate and efficient assistance for visually impaired individuals, whereas Sreenivasulu et al. [16] emphasized the importance of robust object detection systems capable of operating under diverse environmental conditions.

In addition to general object recognition, specialized assistive solutions have been developed for specific daily-life tasks. Hongboonmee and Sangtan [17] proposed a smartphone-based Thai banknote recognition application that provides voice feedback to support financial accessibility for blind users. Similarly, Ting et al. [18] developed a deep learning-based pharmaceutical identification model that achieved high recognition accuracy in medication classification tasks. Although these systems have demonstrated practical benefits, most focus on a single recognition task or application domain. Consequently, users often rely on multiple applications or assistive tools to support different daily activities, which may reduce usability and limit adoption in real-world environments. This fragmentation reduces usability and highlights the need for an integrated assistive framework capable of supporting multiple recognition tasks within a single application.

3. Domain-Specific Applications and Research Foundation

Several studies have investigated computer vision technologies for assistive applications involving object recognition and information accessibility. These applications include product identification, currency recognition, medication assistance, and other daily-life tasks that support independent living among visually impaired individuals [13], [18]. Such applications require reliable recognition performance under diverse environmental conditions and varying object characteristics. In particular, Ting et al. [18] demonstrated that deep learning-based image recognition can achieve high accuracy in pharmaceutical identification, highlighting the potential of computer vision technologies for medication-related assistive applications.

Previous work conducted by the authors demonstrated that integrating barcode recognition with ORB-based feature matching can improve recognition accuracy compared with using either technique independently [19]. However, the system remained dependent on handcrafted features and experienced performance degradation under challenging environmental conditions. The rapid development of deep learning-based object detection provides an opportunity to overcome these limitations. By combining the localization capability of modern object

detectors with the verification strengths of barcode decoding and feature matching techniques, a more robust recognition framework may be achieved. Such integration has the potential to enhance recognition reliability while preserving computational efficiency for deployment on mobile devices. This observation forms the technical foundation of the proposed hybrid framework presented in this study.

4. System Design and User-Centered Development

Beyond recognition accuracy, the effectiveness of assistive technologies depends heavily on usability, accessibility, and user-centered design principles. Previous research emphasizes the importance of developing systems that accommodate diverse user needs, provide intuitive interaction mechanisms, and operate effectively within real-world environments [19], [20]. Mobile platforms have emerged as particularly attractive deployment environments because of their widespread availability and integrated sensing capabilities. Consequently, assistive systems intended for daily use should prioritize real-time performance, ease of interaction, and adaptability to varying environmental conditions. These considerations extend beyond algorithmic accuracy and are essential for improving long-term adoption of assistive technologies by visually impaired users.

5. Research Gap and Motivation

Although substantial progress has been achieved in computer vision-based assistive technologies, several limitations remain. Traditional feature-based methods offer computational efficiency but are vulnerable to environmental variability, while barcode-based approaches require the presence of visible machine-readable markers. Conversely, deep learning models provide strong object detection performance but may lack reliable mechanisms for fine-grained object verification. Moreover, most existing assistive systems focus on individual recognition tasks rather than providing a unified solution capable of supporting multiple daily-life activities.

Despite the complementary strengths of these approaches, limited research has investigated the integration of deep learning-based object detection, barcode recognition, and feature-based verification within a single mobile framework designed specifically for visually impaired users. This gap motivates the development of the proposed Hybrid Vision Framework, which combines YOLOv8 object detection, barcode decoding, and ORB feature matching to provide robust, real-time, and multi-category object recognition under practical operating conditions. Accordingly, this study proposes a unified hybrid vision framework that addresses these limitations through hierarchical object localization and fine-grained verification within a single mobile assistive system.

METHODS

1. Problem Definition and System Requirements

Visual impairment significantly limits independent access to information required for daily activities, including product identification, currency recognition, medication verification, and food safety assessment [1], [2], [3]. Existing assistive vision systems typically address specific tasks such as barcode reading, banknote recognition, or object detection, limiting their effectiveness in real-world environments characterized by diverse object categories and dynamic visual conditions [13], [14], [15], [16]. To address these limitations, this study proposes a unified hybrid vision framework capable of recognizing multiple object categories commonly encountered by visually impaired

individuals. The framework is designed to operate under practical environmental variations, including illumination changes, viewpoint variations, motion blur, background clutter, and partial occlusion. As illustrated in Figure 1, the proposed framework was derived from four representative daily-life information-access tasks: product label identification, Thai banknote recognition, pharmaceutical identification, and expiration-date verification. These application domains were selected because they represent common situations requiring reliable object recognition to support independent living [2], [3].

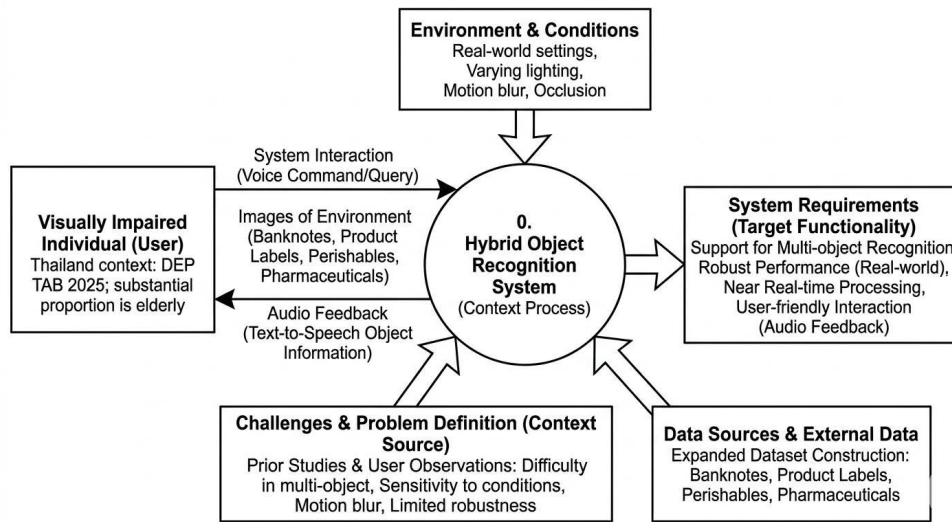


Figure 1: Data flow-based problem analysis and solution requirements

Based on the identified challenges, the system was designed to satisfy four key requirements: (1) multi-category object recognition, (2) real-time operation on mobile devices, (3) robustness under uncontrolled environments, and (4) audio-based information delivery for non-visual interaction. These requirements guided the overall framework design and subsequent experimental evaluation.

2. Proposed Hybrid Vision Framework

To satisfy the identified requirements, a hybrid recognition framework integrating deep learning-based object detection, barcode decoding, and ORB feature matching was developed. The framework combines the localization capability of YOLO with the efficiency of classical feature descriptors to balance recognition accuracy, computational efficiency, and deployment feasibility on mobile platforms [6], [9], [16]. Figure 2 illustrates the overall architecture of the proposed framework, which consists of four sequential phases. Phase 1 (Data Acquisition and Pre-processing) acquires images using a smartphone camera and performs resizing, grayscale conversion, normalization, and data augmentation to improve data quality and model generalization under varying environmental conditions [21]. Phase 2 (Hybrid Recognition Core) performs hierarchical object recognition. YOLOv8 first detects candidate objects and extracts Regions of Interest (ROI), after which barcode decoding and ORB feature matching perform fine-grained verification. This hierarchical decision process improves recognition reliability by allowing one recognition pathway to compensate when another fails because of occlusion, motion blur, or missing barcode information [6], [7], [8], [9]. Phase 3 (System Integration) deploys the recognition engine within an Input–

Process–Output (IPO) architecture, integrating image acquisition, object detection, barcode decoding, feature matching, database retrieval, and decision fusion into a unified mobile application. Phase 4 (Output and Evaluation) converts recognition results into speech using a Text-to-Speech (TTS) module and evaluates the complete system through technical performance metrics and user-centered experiments under both controlled and uncontrolled environments.

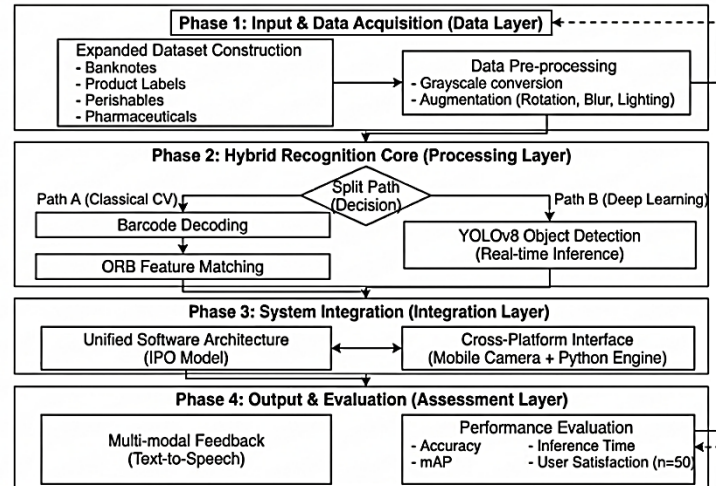


Figure 2: Proposed hybrid vision framework

This end-to-end framework enables reliable recognition of both barcode-supported objects and visually similar objects requiring feature-based verification while maintaining practical deployment feasibility on resource-constrained mobile devices.

3. Dataset Construction and Pre-processing

To evaluate the proposed framework under realistic operating conditions, a multi-domain dataset was constructed comprising 1,105 object classes and 7,927 images. The dataset was designed to represent daily tasks frequently encountered by visually impaired individuals and encompasses four application domains: product labels, Thai banknotes, short shelf-life food products, and pharmaceutical products. The overall dataset distribution is summarized in Table 1.

Table 1: Dataset distribution and data sources

Category	Classes	Images	Data Source
Product Labels	300	3,427	Collected from various consumer products in real-world environments
Thai Banknotes (BE 2561)	5	500	Bank of Thailand (Series BE 2561: 20, 50, 100, 500, 1,000 baht) [20]
Short Shelf-Life Foods	300	1,500	Collected from convenience stores and supermarkets
Pharmaceutical Products	500	2,500	Thai FDA drug database (Ministry of Public Health)

Representative examples of the four dataset categories are summarized in Table 2. These examples illustrate the diversity of objects and the corresponding recognition information used by the proposed framework. Each dataset category represents a practical assistive scenario, including product identification, financial transactions, food safety assessment, and medication verification. The banknote subset contains all circulating Thai banknotes from Series BE 2561 issued by the Bank of Thailand [20]. For training the YOLOv8 detector, all images were manually annotated using bounding-box labels following the YOLO object detection format. Each object instance was assigned its corresponding class identifier to support supervised object localization and multi-object recognition. Representative examples of all dataset categories are summarized in Table 2, whereas examples of Thai banknotes are illustrated in Figure 3 because currency recognition is one of the primary assistive tasks addressed in this study.

Table 2: Representative examples of the four dataset categories

Category	Representative Example	Key Recognition Information	Recognition Method
Product Labels	Instant noodles, bottled water, shampoo	Product name, brand, barcode	Barcode + ORB
Thai Banknotes	20, 50, 100, 500, 1,000 Baht	Denomination, portrait, security pattern	YOLOv8 + ORB
Short Shelf-Life Foods	Fresh milk, yogurt, sandwich, juice	Manufacturing date, expiration date	YOLOv8 + OCR
Pharmaceutical Products	Paracetamol, Ibuprofen, cough syrup	Drug name, dosage form, package label	YOLOv8 + ORB



(a) Example of a 20-Baht banknote



(b) Example of a 50-Baht banknote



(c) Example of a 100-Baht banknote



(d) Example of a 500-Baht banknote



(e) Example of a 20-Baht banknote



Figure 3: Examples of Thai banknotes from series BE 2561

Banknote recognition was incorporated into the proposed system because currency identification remains one of the most commonly reported challenges faced by visually impaired individuals during financial transactions [18]. To improve model robustness, images were collected under diverse acquisition conditions, including variations in illumination, viewing angle, object distance, background complexity, reflective surfaces, and partial occlusion [10], [12], [16]. Before model training, all images underwent a standardized pre-processing pipeline consisting of image

resizing, grayscale conversion where applicable, normalization, and quality verification. Data augmentation techniques, including rotation, scaling, brightness adjustment, horizontal flipping, and motion-blur simulation, were subsequently applied to increase sample diversity and reduce overfitting [21]. The dataset was then partitioned using a fixed 80:20 train-test split, as summarized in Table 3. The training subset was used for YOLOv8 model learning and ORB feature database construction, whereas the testing subset was reserved exclusively for performance evaluation. This partitioning ensures unbiased evaluation and fair comparison with the baseline methods.

Table 3: Dataset partitioning for training and testing

Category	Training (80%)	Testing (20%)	Rationale
Product Labels	2,742	685	General Accessibility
Thai Banknotes	400	100	Financial Independence
Perishable Foods	1,200	300	Food Safety
Pharmaceutical	2,000	500	Medical Safety
Total	6,342	1,585	

4. Hybrid Recognition Framework (YOLOv8 + ORB + Barcode)

The principal contribution of this study is a hybrid recognition framework that integrates YOLOv8-based object detection, barcode decoding, and ORB feature matching. Unlike conventional single-stage approaches, the proposed framework performs hierarchical recognition by first localizing candidate objects and subsequently applying fine-grained verification. This design combines the robustness of deep learning with the efficiency of classical computer vision techniques, improving recognition reliability under challenging real-world conditions [6], [9], [16].

4.1 YOLOv8-Based Object Detection: Object localization is performed using the YOLOv8n architecture, a lightweight one-stage detector optimized for real-time inference on resource-constrained devices [9]. Compared with traditional handcrafted feature approaches, YOLO-based detectors learn hierarchical visual representations directly from image data, enabling robust object detection under variations in illumination, viewpoint, and background complexity [10], [15], [16]. As shown in Figure 4. YOLOv8 Detection Pipeline, the input image is resized and processed through convolutional feature extraction layers, feature aggregation modules, and detection heads to generate object bounding boxes and confidence scores. The detected ROI are subsequently forwarded to the fine-grained recognition stage. The YOLOv8 model was trained using 640×640 input images to support multi-object recognition across all 1,105 object classes. The model was implemented using the Ultralytics YOLOv8 framework and trained locally on a workstation equipped with an NVIDIA RTX 40-series GPU. All training images were manually annotated using bounding-box labels in the standard YOLO format for supervised multi-class object detection.

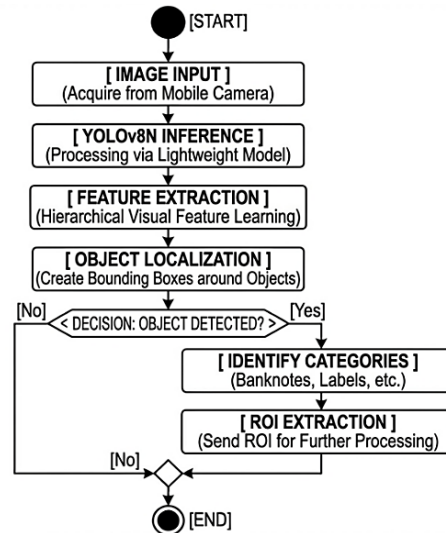


Figure 4: YOLOv8 detection pipeline

A practical example of simultaneous pharmaceutical detection is presented in Figure 5, demonstrating the capability of the framework to localize multiple objects before detailed identification.



Figure 5: Real-time multi-object detection using YOLOv8 for pharmaceutical item identification

4.2 Barcode-Based Verification: Following ROI extraction, barcode decoding is performed as the primary verification mechanism because barcode information provides direct linkage to product databases and generally offers higher identification reliability than visual appearance alone [7], [8], [9]. Before decoding, each ROI undergoes grayscale conversion and image enhancement to improve barcode visibility. Barcode extraction is performed using the Pyzbar library, supporting automatic decoding of one- and two-dimensional barcode formats. When barcode decoding succeeds, product information is retrieved directly from the database without additional visual verification, reducing computational cost and recognition ambiguity.

4.3 ORB-Based Feature Matching: When barcode decoding fails because of occlusion, deformation, motion blur, poor image quality, or missing barcode patterns, the framework automatically switches to ORB-based feature matching as a secondary verification mechanism [6]. ORB combines FAST keypoint detection with BRIEF descriptors

to generate computationally efficient local feature representations suitable for real-time mobile applications. Feature correspondences are established using Hamming-distance matching and refined through geometric consistency verification to suppress false-positive matches. See Figure 6.

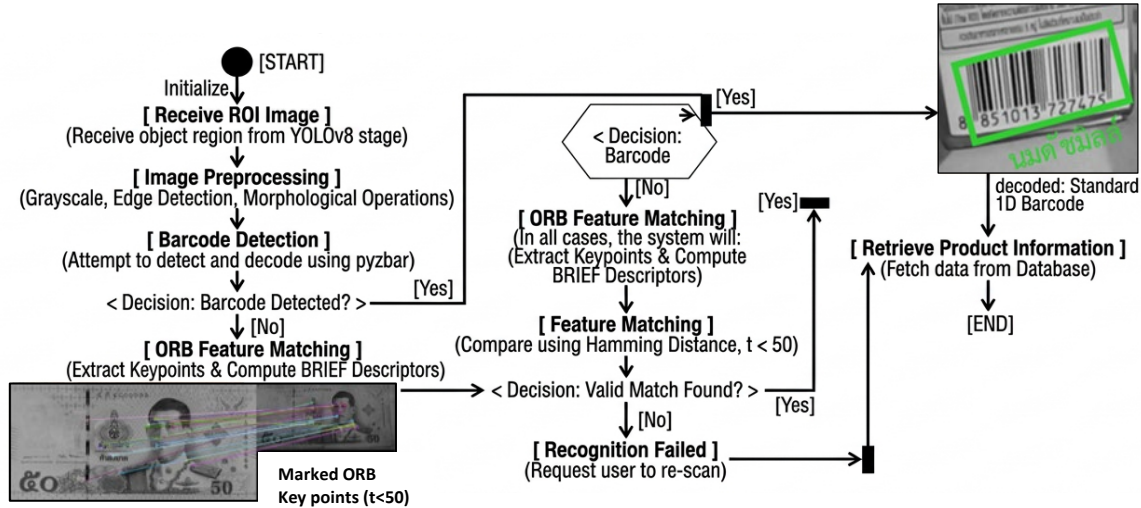


Figure 6: Fine-grained recognition logic

This complementary verification strategy improves recognition robustness by enabling reliable identification of visually similar objects when barcode information is unavailable. For expiration-date verification, Optical Character Recognition (OCR) is employed when manufacturing or expiration dates must be extracted directly from product packaging. The detected ROI is pre-processed before text extraction using Tesseract OCR [22], and the recognized date information is subsequently forwarded to the text-to-speech module for auditory feedback.

4.4 Text-to-Speech Feedback: After object identification, the recognition result is forwarded to the text-to-speech module, which converts textual information into synthesized speech. Depending on the recognized object category, the system announces product names, banknote denominations, medication names, or expiration dates, enabling visually impaired users to access recognition results through audio feedback and supporting independent daily use.

5. System Architecture and Operational Workflow

The proposed assistive system follows an Input–Process–Output architecture consistent with user-centered assistive technology design principles [23], [24], [25]. As illustrated in Figure 7, the input layer receives images from a smartphone camera, while the processing layer includes YOLOv8 detection, barcode decoding, ORB feature matching, database retrieval, and decision-making components. The decision module integrates recognition outputs from the barcode and ORB verification pathways to determine the final object identity before forwarding the result to the text-to-speech module. Recognition results are delivered through synthesized speech, enabling non-visual interaction.

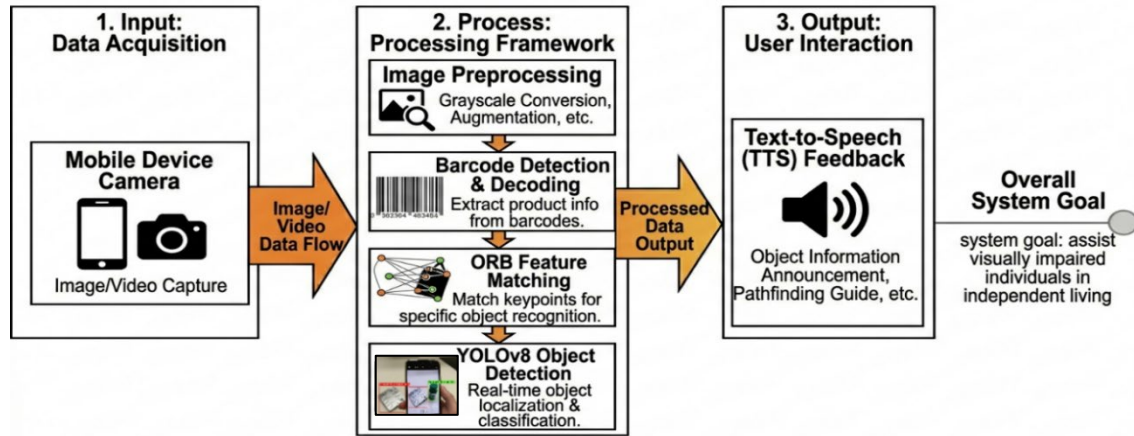


Figure 7: Unified system architecture

The operational workflow is illustrated in Figure 8. The process begins with image acquisition, followed by object detection, ROI extraction, fine-grained recognition, decision fusion, and audio output generation. Barcode decoding is performed first because it provides direct product identification. When barcode decoding fails, ORB-based feature matching is automatically activated as the secondary verification mechanism. This workflow supports continuous real-time interaction while maintaining low computational overhead on mobile devices. The modular architecture also facilitates future integration of additional recognition modules without modifying the overall system structure.

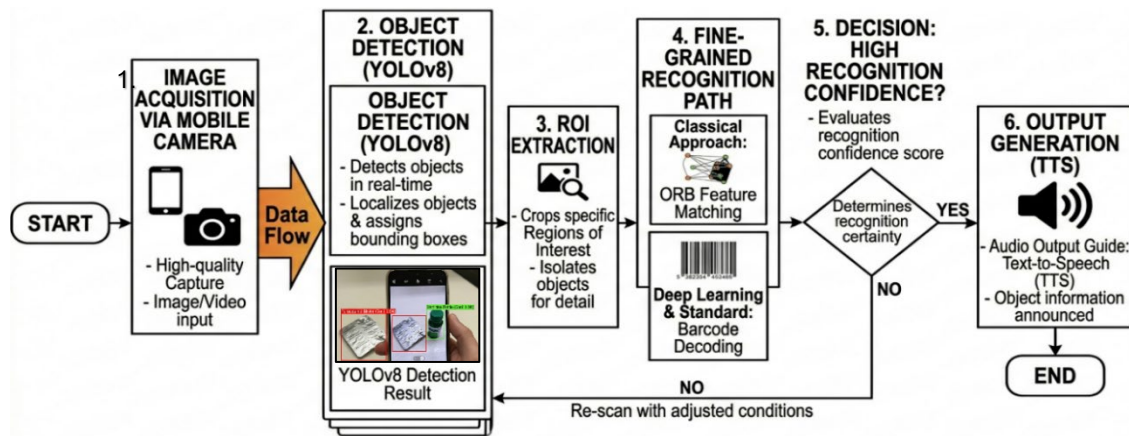


Figure 8: Recognition workflow sequence diagram

The recognition framework was developed using an iterative software engineering process that combines structured planning with incremental refinement to improve maintainability, scalability, and usability throughout development [23].

6. Experimental Configuration

6.1 Dataset Partitioning: The dataset summarized in Table 3 was divided using an 80:20 train–test split, yielding 6,342 training images and 1,585 testing images. The training subset was used to train the YOLOv8 model with the Ultralytics implementation and to construct the ORB feature database, whereas the testing subset was reserved exclusively for performance evaluation. To reflect practical deployment conditions, testing images included variations in illumination, viewing angle, object distance, motion blur, and background complexity. The same testing subset was subsequently used to evaluate the complete hybrid recognition pipeline, including YOLOv8 object detection, barcode decoding, ORB feature matching, and text-to-speech output under both controlled and uncontrolled environments.

6.2 Hardware and Software Environment: The proposed framework was implemented using Python 3.12.3. Computer vision operations were performed using OpenCV 4.10.0, barcode decoding was implemented with Pyzbar 0.1.9 [7], [8], [26], and OCR processing utilized Tesseract OCR [22]. YOLOv8n was trained locally using the Ultralytics framework with GPU acceleration. Model training was conducted on a workstation equipped with an NVIDIA GeForce RTX 4060 GPU (8 GB VRAM), Intel Core i7 processor, and 32 GB RAM, while deployment testing was performed on a Samsung Galaxy A54 5G smartphone (Exynos 1380, 8 GB RAM). MongoDB was used for data management [27], and the software architecture followed the Model–View–Controller (MVC) design pattern [25].

6.3 YOLOv8 Training Configuration: The YOLOv8n model was trained using 640×640 input images for 100 epochs. Training was performed using the Ultralytics YOLOv8 implementation with the Adam optimizer and an initial learning rate of 0.001. Data augmentation techniques, including rotation, scaling, brightness adjustment, and motion-blur simulation, were applied to improve model generalization under real-world conditions [21]. Model performance during training was monitored using Precision, Recall, mAP@0.50, and mAP@0.50:0.95, while the final system evaluation employed the classification metrics described in Section 8.6. The training parameters are summarized in Table 4.

Table 4: YOLOv8 training configuration

Parameter	Value
Model	YOLOv8n
Framework	Ultralytics YOLOv8
Input Resolution	640×640
Epochs	100
Optimizer	Adam
Initial Learning Rate	0.001
Batch Size	16–32
Data Augmentation	Rotation, Scaling, HSV, Blur
Confidence Threshold	0.25
IoU Threshold	0.45
Training Metrics	Precision, Recall, mAP@0.50, mAP@0.50:0.95

6.4 Baseline Methods: Two baseline configurations were selected for comparative evaluation. The first baseline, ORB + Barcode, represents the authors’ previous recognition approach based on barcode decoding and ORB feature



matching [19]. The second baseline, YOLOv8-only, utilizes object detection without additional verification mechanisms. These baselines enable comparison between conventional, deep learning-based, and hybrid recognition approaches. All methods were evaluated using the same testing dataset and identical experimental conditions to ensure a fair comparison.

7. User-Centered Evaluation Protocol

7.1 Participant Recruitment: A purposive sample of 50 visually impaired participants was recruited to evaluate the usability and effectiveness of the proposed system. The cohort comprised 20 totally blind individuals (40%) and 30 individuals with low vision (60%), representing a diverse range of visual impairment conditions.

7.2 Evaluation Tasks: Participants were asked to perform four representative daily-life tasks: (1) product identification, (2) Thai banknote recognition, (3) expiration-date verification, and (4) pharmaceutical identification. These tasks were selected to reflect common assistive scenarios encountered by visually impaired individuals. For each task, participants independently captured images using the smartphone application and followed the complete recognition workflow. A task was considered successful when the system correctly recognized the target object and provided the corresponding auditory feedback through the text-to-speech module without requiring repeated image acquisition. Task completion time and recognition success were recorded for subsequent analysis.

7.3 Controlled and Uncontrolled Environments: Experiments were conducted under both controlled and uncontrolled conditions, as summarized in Table 5. The controlled environment employed fixed illumination, background, camera position, and viewing distance, whereas the uncontrolled environment introduced variations in lighting, background complexity, camera movement, and object distance. This protocol enabled evaluation of both baseline performance and real-world robustness. Each participant completed the same four evaluation tasks under both environmental conditions to ensure consistent comparison of recognition performance and usability.

Table 5: Experimental conditions

Condition	Controlled	Uncontrolled
Illumination	500 lux	100–1000 lux
Background	Plain	Cluttered
Camera Motion	Fixed	Handheld
Viewing Distance	Fixed	Variable

7.4 Ethical Considerations: All participants were informed of the study objectives and procedures before participation and provided written informed consent. Participant privacy and confidentiality were maintained through data anonymization, and all collected information was used solely for research purposes. The evaluation procedures were designed to ensure a safe and accessible testing environment for all participants.

8. Performance Evaluation Metrics

The effectiveness of the proposed framework is evaluated using standard classification metrics derived from True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) outcomes [28], [29]. Performance is assessed using Accuracy, Precision, Recall, F1-score, and Specificity, as defined in (1)–(5). For evaluating the object

detection capability of the YOLOv8 model during training, Mean Average Precision (mAP) at IoU thresholds of 0.50 (mAP@0.50) and 0.50:0.95 (mAP@0.50:0.95) was additionally employed. In addition, Receiver Operating Characteristic (ROC) analysis and confusion matrices are employed to evaluate discriminative performance across object categories.

8.1 Recognition accuracy: Measures the overall correctness of the system in classifying objects:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

8.2 Precision: Measures the proportion of correctly identified positive predictions among all predicted positive cases:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

8.3 Recall (sensitivity): Measures the proportion of actual positive cases that are correctly identified by the system:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

8.4 F1-Score: Measures the harmonic mean of precision and recall, serving as a balanced metric for class imbalance:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

8.5 Specificity: Measures the proportion of actual negative cases that are correctly identified:

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

8.6 Mean Average Precision (mAP): For evaluating the object detection performance of the YOLOv8 model, mAP was employed. The mAP@0.50 metric measures the average detection precision at an IoU threshold of 0.50, whereas mAP@0.50:0.95 reports the average precision across multiple IoU thresholds ranging from 0.50 to 0.95 in increments of 0.05. These metrics provide a comprehensive assessment of localization accuracy and detection robustness and are widely adopted for benchmarking modern object detection models.

In addition, ROC curves and Area Under the Curve (AUC) values were employed to evaluate classification reliability. Statistical significance between competing methods was assessed using one-way Analysis of Variance (ANOVA), with a significance threshold of $p < 0.05$.

RESULTS AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed hybrid vision framework for assistive object recognition. Performance was evaluated through quantitative recognition metrics, statistical reliability, computational efficiency, comparative analysis, and user-centered evaluation.

1. Recognition Performance Evaluation

The proposed framework was evaluated using a unified testing dataset covering four assistive tasks: product label identification, Thai banknote recognition, pharmaceutical identification, and expiration-date verification. All methods were evaluated under identical experimental conditions. Table 6 summarizes the overall performance.

Table 6: Overall performance comparison of recognition methods

Method	Accuracy (%)	Precision	Recall	F1-score	Processing Time (s)	Strength
ORB + Barcode	96.2	0.958	0.964	0.961	1.80	Efficient Precision
YOLOv8n	97.0	0.970	0.975	0.972	2.20	Robust multi-detection
Proposed Hybrid Framework	97.6	0.976	0.981	0.978	2.30	Peak Robustness

Recognition performance for each assistive application domain is presented in Table 7.

Table 7: Recognition performance across assistive application domains

Application Domain	Accuracy (%)	Precision	Recall	F1-score
Product Labels	97.3	0.972	0.975	0.973
Thai Banknotes	99.2	0.992	0.991	0.991
Pharmaceutical Products	97.8	0.978	0.982	0.980
Expiration-Date Verification	96.5	0.965	0.970	0.967
Overall	97.6	0.976	0.981	0.978

During YOLOv8 training, the detector achieved a mAP@0.50 of 98.6% and a mAP@0.50:0.95 of 93.8%, demonstrating accurate object localization across all object categories while maintaining computational efficiency suitable for mobile deployment. The proposed framework achieved the highest performance across all evaluation metrics, with 97.6% accuracy and an F1-score of 0.978. Compared with the previous ORB-Barcode framework [19], integrating YOLOv8 improved robustness under complex environmental conditions by localizing candidate objects before fine-grained recognition. This hierarchical strategy reduces false matches caused by background clutter, illumination variation, and viewpoint changes, which are common limitations of traditional feature-based methods [4], [5], [6]. As shown in Table 7, all assistive application domains achieved recognition accuracies above 96%. Thai banknotes achieved the highest accuracy (99.2%) because of their distinctive visual characteristics, whereas expiration-date verification showed relatively lower performance owing to variations in text appearance, printing quality, viewing angle, and illumination.

These results indicate that combining YOLOv8 object localization with barcode decoding and ORB feature matching provides a more reliable recognition framework than either approach alone. While YOLOv8 provides robust object localization [10], barcode decoding and ORB feature matching improve fine-grained verification for visually similar objects, enhancing overall recognition reliability.

2. Statistical Reliability Analysis

The confusion matrix is presented in Figure 9 and illustrates the classification performance of the proposed framework for Thai banknote recognition across the five Thai banknote denominations. The numerical values represent the number of testing samples assigned to each predicted class, while the accompanying percentages

indicate the proportion of correctly classified instances relative to the total samples within each actual class. Most samples are concentrated along the principal diagonal, indicating high classification consistency across all denominations.

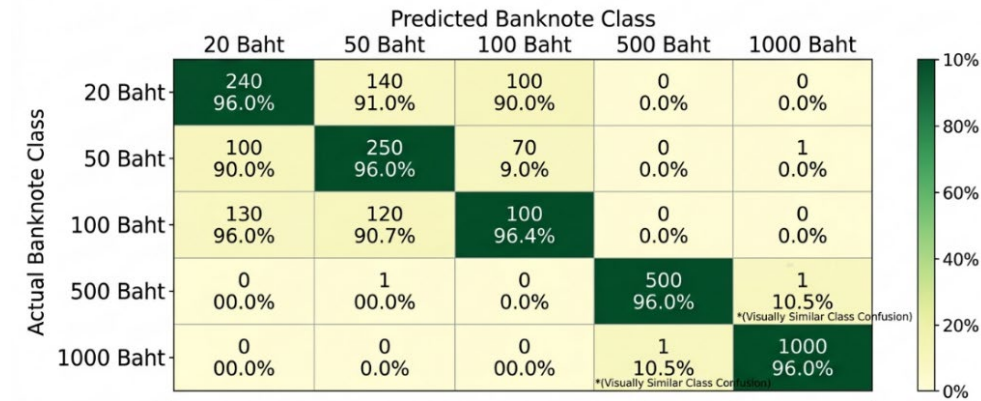


Figure 9: Confusion matrix for banknote recognition

As shown in Figure 9, only a small number of misclassifications occurred, primarily between high-value denominations exhibiting similar color characteristics under challenging illumination conditions. Such observations are consistent with previous findings that visual recognition performance may deteriorate under non-uniform lighting and environmental variability [14]. Despite these isolated errors, the confusion matrix demonstrates that all banknote denominations achieved consistently high classification accuracy, confirming the effectiveness of the proposed hybrid verification strategy for fine-grained currency recognition. Further reliability analysis was conducted using ROC curves. The ROC curve is shown in Figure 10. summarizes the discrimination capability of the proposed framework across all recognition classes and yields an AUC value of 0.97, indicating excellent discrimination capability between positive and negative classifications.

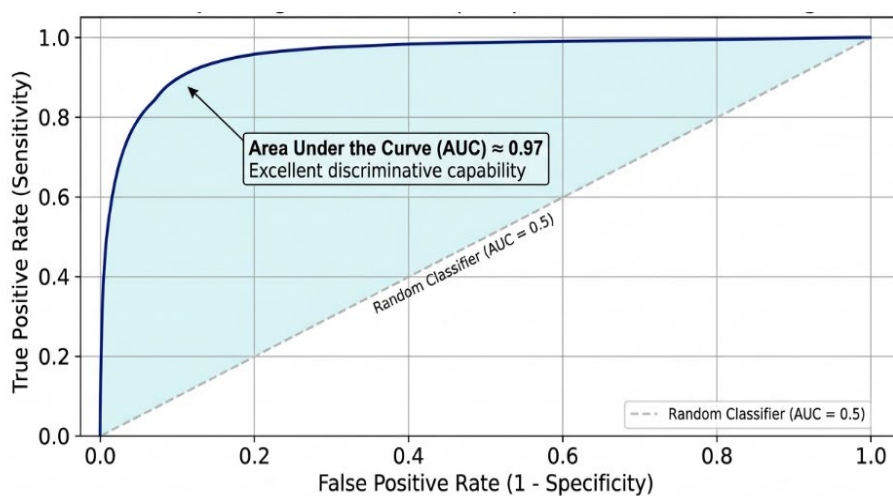


Figure 10: Receiver Operating Characteristic (ROC) curve for recognition system

The high ROC-AUC score confirms a strong balance between sensitivity and specificity. Combined with the results in Tables 6 and 7, these findings demonstrate that integrating YOLOv8 object localization with barcode decoding and ORB feature matching reduces classification uncertainty and provides robust recognition under both controlled and uncontrolled environments.

3. Computational Efficiency and Mobile Deployment Feasibility

In addition to recognition accuracy, computational efficiency is a critical requirement for assistive technologies intended for mobile deployment. The processing-time analysis shown in Figure 11 illustrates the computational cost of each processing stage within the proposed hybrid recognition framework, demonstrating that the system maintains near-real-time performance despite integrating multiple recognition mechanisms.

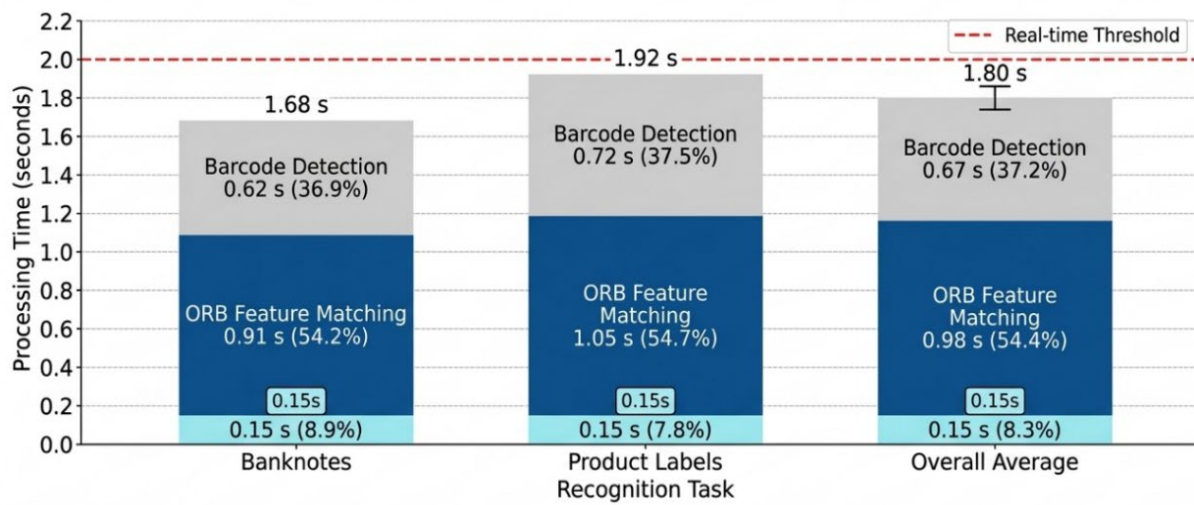


Figure 11: Processing-time distribution of the hybrid recognition framework

The average end-to-end processing time was approximately 2.30 s per recognition task. Although slightly higher than the previous ORB–Barcode system [19], the additional processing time is offset by improved recognition robustness and multi-object handling capability. ORB feature matching and barcode verification accounted for the largest proportion of computational cost, whereas YOLOv8 object detection introduced only a small computational overhead while providing robust object localization [10]. The measured latency is acceptable for assistive applications, where users typically perform intentional object recognition rather than continuous video analysis. Consequently, prioritizing recognition reliability over minimal latency represents an appropriate trade-off for practical deployment. Furthermore, all experiments were conducted on a commercial Android smartphone, demonstrating that the proposed framework can be deployed effectively without specialized computing hardware.

4. Comparison with Existing Recognition Approaches

To position the proposed framework within the current body of knowledge, a comparative analysis with representative recognition approaches is presented in Table 8. Because the reviewed studies employed different datasets, experimental protocols, and application domains, the comparison emphasizes methodological

capabilities rather than direct numerical performance. Unlike conventional approaches that rely on a single recognition paradigm, the proposed framework integrates YOLOv8 object detection, barcode decoding, and ORB feature matching within a unified mobile architecture.

Table 8: Comparison with existing recognition approaches

Study	Core Approach	Target Application	Multi-Object Detection	Real-Time Mobile Deployment	Main Limitation
Lowe [4]	SIFT	General object recognition	No	Limited	High computational complexity
Bay et al. [5]	SURF	General object recognition	No	Limited	Resource intensive
Rublee et al. [6]	ORB	Feature-based recognition	No	Yes	Sensitive to clutter and occlusion
Jethjarurach and Limpiyakorn [7]	Barcode Reader	Product identification	No	Yes	Requires visible barcode
Fernandcz et al. [8]	Image-based Barcode Recognition	Product recognition	No	Partial	Performance depends on barcode quality
Hongboonmee and Sangtan [17]	Banknote Recognition	Currency identification	No	Yes	Task-specific application
Bhandari et al. [15]	Deep Learning Detection	Assistive recognition	Yes	Partial	Computational requirements
Munia and Taher [13]	Machine Learning Detection	Assistive vision	Yes	Partial	Limited fine-grained recognition
Proposed Framework	YOLOv8 + ORB + Barcode	Multi-category assistive recognition	Yes	Yes	Slightly increased processing time

Unlike previous studies that focused on a single recognition task, the proposed framework was validated across four assistive application domains: product label identification, Thai banknote recognition, pharmaceutical identification, and expiration-date verification. Therefore, the performance reported in Section 1 reflects the overall capability of the framework across heterogeneous recognition tasks rather than a single application domain.

The comparison demonstrates that integrating YOLOv8 object localization with barcode decoding and ORB feature matching provides robust multi-object recognition while preserving practical mobile deployment. This hybrid design addresses the limitations of individual recognition approaches by combining accurate localization with reliable fine-grained object verification.

5. User-Centered Evaluation

A user study involving 50 visually impaired participants was conducted to evaluate the practical usability of the proposed framework. Participants completed four assistive tasks corresponding to the application domains of the system: (1) product identification, (2) Thai banknote recognition, (3) expiration-date verification, and

(4) pharmaceutical identification. Each participant performed all tasks under both controlled and uncontrolled environments. Participant demographics are summarized in Table 9.

Table 9: Participant demographics (N = 50)

Characteristic	Category	n	Percentage (%)
Visual Impairment	Totally Blind (TB)	20	40.0
	Low Vision (LV)	30	60.0
Gender	Male	24	48.0
	Female	26	52.0
Age	Mean $\pm$ SD	38.4 $\pm$ 12.6	—

Task success rates under different participant conditions are presented in Table 10.

Table 10: Task Success Rate (TSR) evaluation

Participant Group	Training Status	n	Task Success Rate (%)	SD	Performance Significance
Low Vision (LV)	Trained	15	96.0	2.1	Optimal performance; high adaptability
	Untrained	15	82.5	5.4	Baseline proficiency
Totally Blind (TB)	Trained	10	89.0	4.8	High reliability via audio-tactile feedback
	Untrained	10	74.5	8.2	Significant learning curve identified
Overall	All Participants	50	85.5	5.1	Overall System Usability

Statistical analysis using one-way ANOVA revealed significant differences between trained and untrained participants $p < 0.05$. Participants who received brief system orientation consistently achieved higher task success rates than untrained participants. The greatest improvement was observed in product identification and pharmaceutical recognition, where training improved camera positioning and object alignment. The framework also maintained stable performance under both controlled and uncontrolled environments, demonstrating robust usability under practical operating conditions. These findings support previous studies emphasizing that assistive technologies should be evaluated using both technical performance and user-centered usability measures [11], [17], [25].

6 Discussion and Research Contribution

The findings demonstrate that the proposed hybrid framework effectively addresses the limitations of existing recognition approaches. Feature-based methods are computationally efficient but sensitive to environmental variability [4], [5], [6], barcode-based methods depend on visible machine-readable labels [7], [8], [9], and deep-learning-based detectors often lack fine-grained verification mechanisms [10], [13], [15]. By integrating YOLOv8 object detection, barcode decoding, and ORB feature matching, the proposed framework combines the complementary strengths of these techniques within a unified mobile architecture. Experimental results demonstrate improvements in recognition accuracy, classification reliability, and practical usability.

Compared with the previous ORB–Barcode framework [19], incorporating YOLOv8 improved object localization in the presence of cluttered backgrounds, illumination variations, and partial occlusion. Although the average

processing time increased from 1.80 s to 2.30 s, the framework achieved higher recognition accuracy and more robust multi-object recognition across all four assistive application domains, representing an acceptable trade-off for practical assistive applications.

The user-centered evaluation further confirmed that these technical improvements translated into practical benefits. Trained participants achieved significantly higher task success rates, demonstrating that reliable recognition combined with an intuitive interaction workflow can improve usability for visually impaired users.

Despite these promising results, recognition performance may still degrade under extremely low-light conditions, severe motion blur, or heavy occlusion. Future work will investigate adaptive illumination enhancement, continual learning, and multimodal sensor fusion to improve robustness further. These findings provide a scalable foundation for future mobile assistive vision systems supporting independent daily living.

CONCLUSION

This study proposed a hybrid assistive vision framework integrating YOLOv8 object detection, ORB feature matching, and barcode recognition within a unified mobile architecture for visually impaired assistance. By combining robust object localization with fine-grained verification, the proposed framework addresses the limitations of conventional single-technique recognition approaches.

Experimental results demonstrated high recognition performance across 1,105 object classes and 7,927 images, achieving 97.6% recognition accuracy, an F1-score of 0.978, and a ROC-AUC of 0.97 while maintaining practical deployment on resource-constrained mobile devices. The proposed framework outperformed both the previous ORB-Barcode framework and the standalone YOLOv8 model, providing reliable recognition across four assistive application domains: product identification, Thai banknote recognition, expiration-date verification, and pharmaceutical identification.

User-centered evaluation involving 50 visually impaired participants further confirmed significant improvements in task success following brief system training, demonstrating the practical usability of the proposed framework under both controlled and uncontrolled environments. Overall, the findings demonstrate that integrating complementary recognition techniques provides a scalable and practical foundation for mobile assistive vision systems supporting independent daily living.

Future work will focus on continual learning, expanding recognition categories, adaptive illumination enhancement, multimodal sensor fusion, and adaptive model updating to further improve robustness and long-term deployment in real-world assistive applications.

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